

An aerial photograph of a city, likely New York City, with a prominent blue overlay. The image shows a dense urban landscape with numerous buildings and streets. The blue overlay is semi-transparent, allowing the city details to be visible underneath. The text is centered on the image.

Making Smart Mobility Smarter, Faster

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Funded by US DOE VTO
David Anderson

System Considerations Critical for Automated, Connected, Efficient and Shared Mobility



As Mobility and Technology Evolves, so Must Analytical Tools for New Knowledge

Single Vehicle



Corridor / Small Network



Entire Urban Area



- Vehicle energy consumption, performance and cost
- Only commercial tool with vehicle level control
- Licensed to >250 companies



RoadRunner

- Only system simulation of multi-vehicles and their environment focused on advanced control enabled by V2V, V2I...
- Uses Autonomie powertrain models



POLARIS

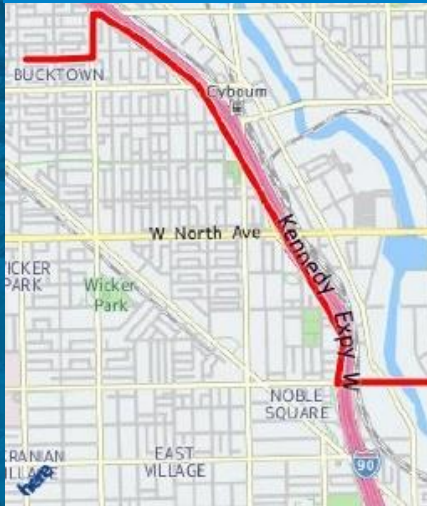
- Agent-based mesoscopic traffic flow simulation
- Focus on traveler behavior, transport modes, technologies

Predict Vehicle Trip Profile

- Supports Eco-Routing
- Required for Predictive Control



Trip definition Origin,
destination, waypoints



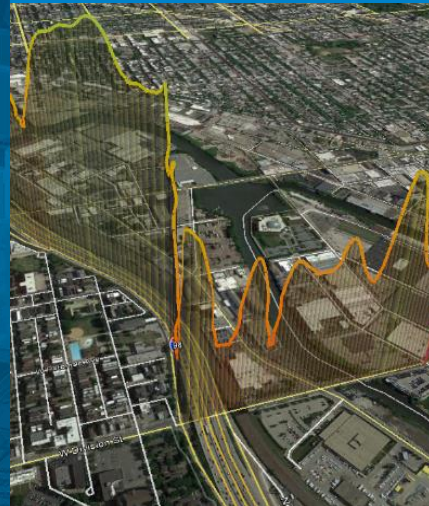
HTTP REST
query



Route data
and data tiles

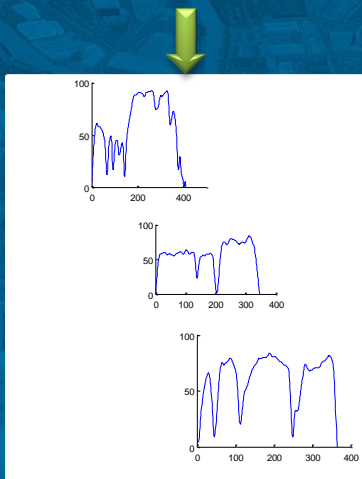


Naturalistic Speed Trace
with Grade



Real-World Stochastic Aspect Introduced by Constrained Markov Chains (SVTrip)

Chicago Travel Survey
(10k vehicle trips, 6M data points)

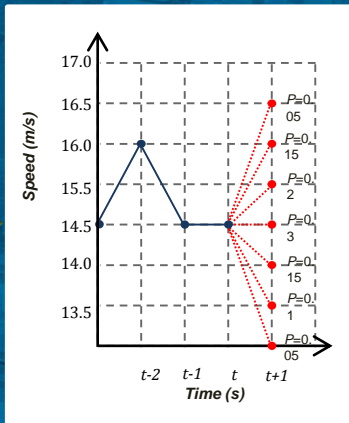


Valid Real-World Micro-Trips

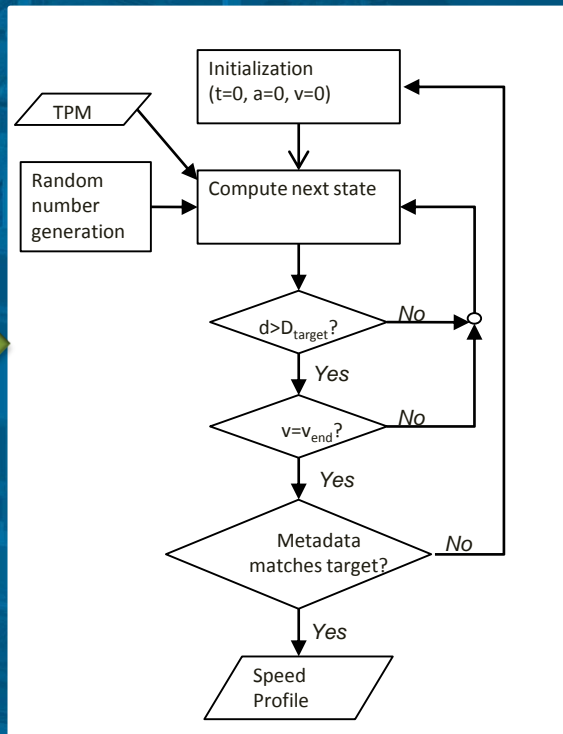
A diagram showing a green arrow pointing from the 'Valid Real-World Micro-Trips' section to a 'Transition Probability Matrix' table. The table is a 4x4 matrix with values ranging from 0.0 to 0.1.

0.0	0.0	...	0.0
5	5	...	5
0.0	0.0	...	0.0
1	0.0	...	0.0
2	2	...	2
...
0.0	0.0	...	0.1
3	7	...	5

Transition
Probability Matrix



Markov Chains

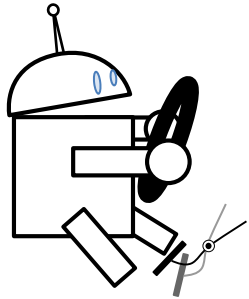
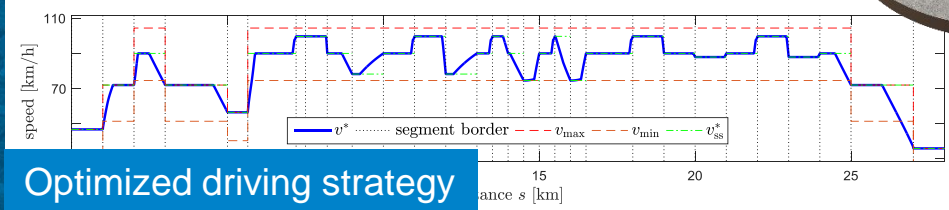


Constrained Markov Chain

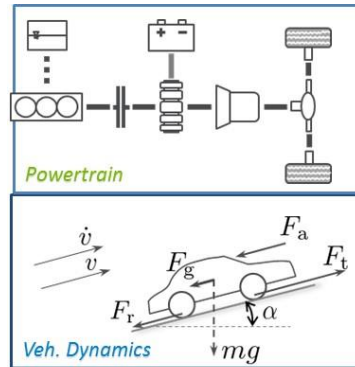
Model Predictive Control Used to Minimize Energy Consumption



Road Horizon
(grade, speed limit)



Automated Driving

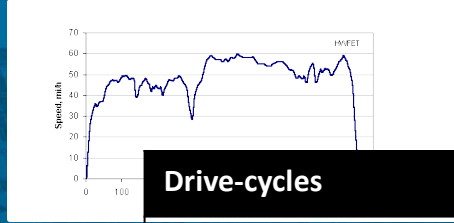


Optimal Control



Fuel savings compared
to baseline control

Modeling CAV Operations



Drive-cycles

- Direct changes to the drive cycles can model CAVs
- Modeling of interactions, control of speed, etc. impossible



Traffic-flow microsimulation

- Can model interactions between vehicles and infrastructure (to some extent)
- Expensive to build (and run)
- Can include powertrain models/control only in compiled form

**Powertrain/Energy
Accuracy**

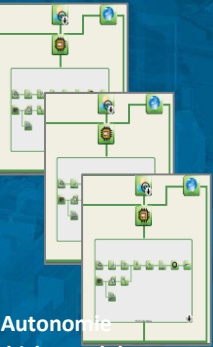
RoadRunner

- Simulate both powertrain and driving interactions
- Easily run a broad range of route scenarios
- Integrate with Autonomie powertrain models
- Provide an environment for development and evaluation of **eco-driving** algorithms for CAVs

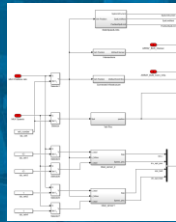
**Traffic
Accuracy**

RoadRunner: Autonomie-Like Closed-Loop CAV Simulation Framework

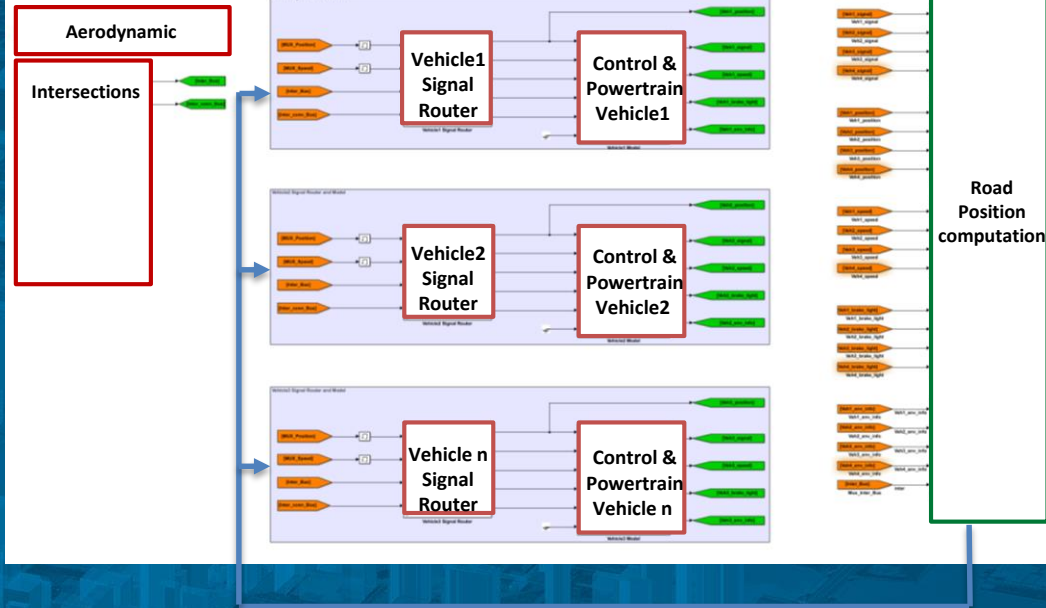
Input Data



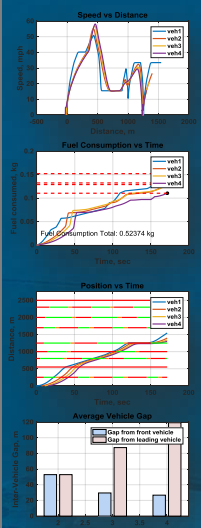
Automated Model Building



Scenario Simulation



Visualization

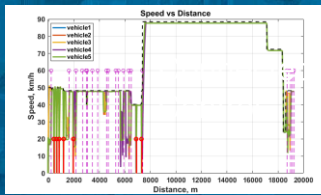
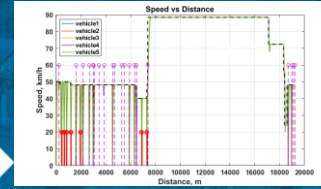
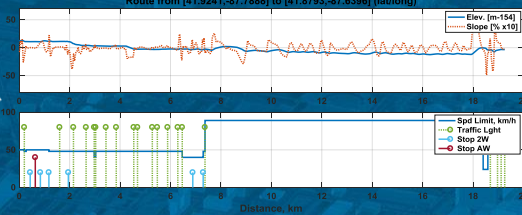


Powertrain Operations in Connected & Automated Driving

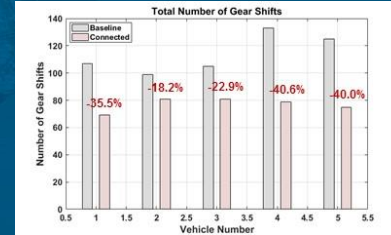
Preliminary Analysis Shows Both Positive & Negative Impacts on Component Operating Conditions due to Eco-Driving

Select Route #1

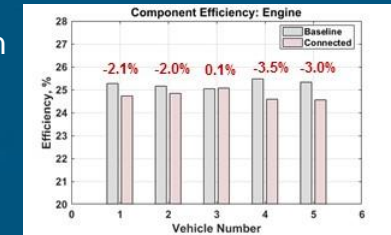
Extract Information



Decrease
in Number
of Shifting
Events



Decrease in
Engine
Cycle
Efficiency

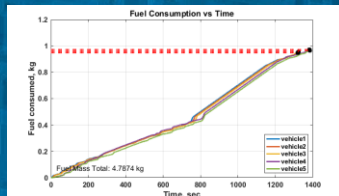


Energy Gains Highly Dependent on Scenarios

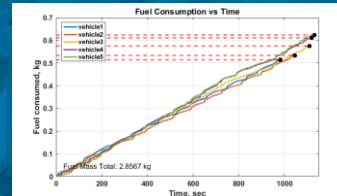
Select Route #2

4.8% gains for Route #1

9.2% gains for Route #1



VS



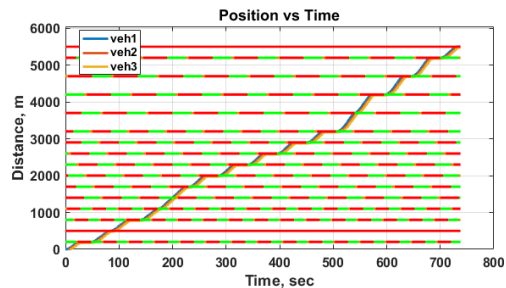
Scenarios also include # of vehicles, powertrain configurations, component technologies, control...

Energy Impact of V2V, V2I, I2V

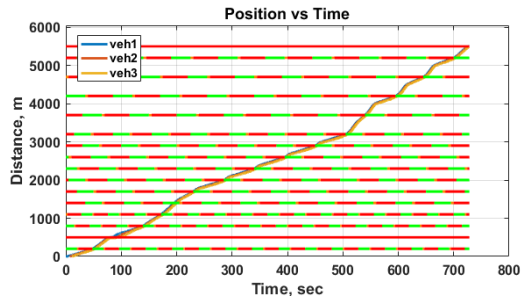


EcoSignal

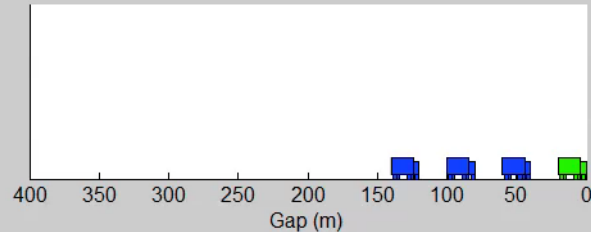
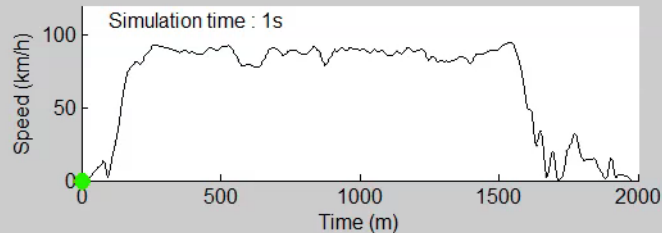
(1) Reference Vehicle



(2) Connected Vehicle



Platooning

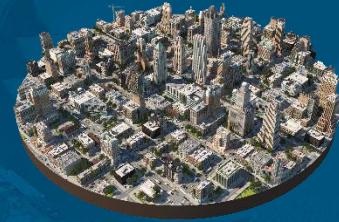


The background of the slide is an aerial photograph of a city, likely San Francisco, with a semi-transparent blue overlay. The text and logo are white, providing high contrast against the blue background.

POL:RIS

**High-Performance, Agent-Based
Simulation of Travelers and
Transportation Systems**

Mobility, Energy and Economic Impact at the Metropolitan Area



Mobility Impact

Population and vehicle synthesis



Activity demand generation



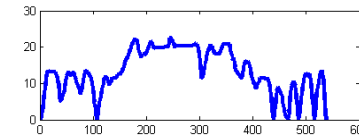
Traffic Flow



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Stochastic
Vehicle Trip
(SVTrip)

Real-World Drive Cycles



Fleet Definition



Energy and Economic Impact

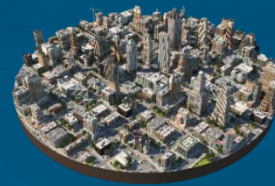
Chicago >



06:00:00



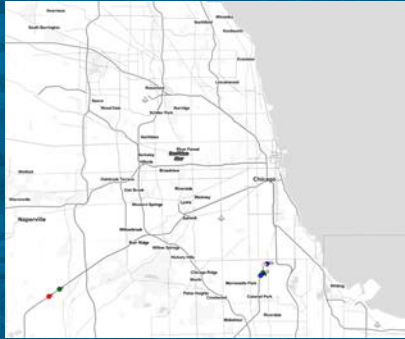
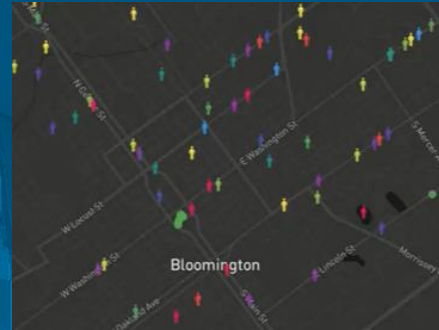
Examples of Future Mobility Scenarios Analyzed



Impact of coordinated platooning
and CACC on energy use

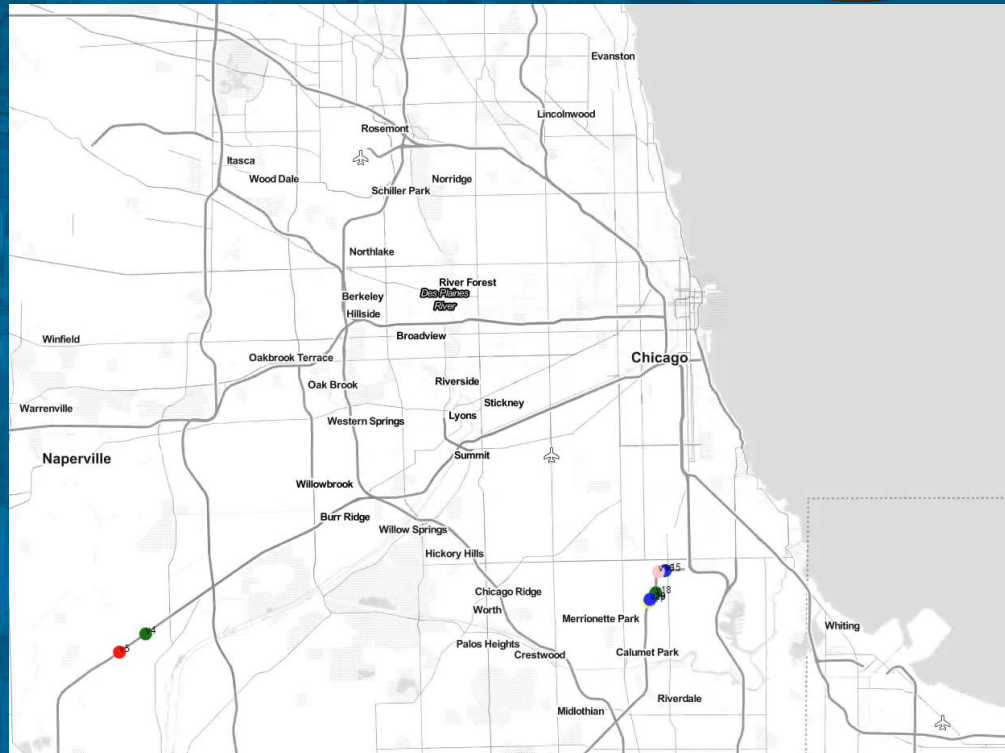
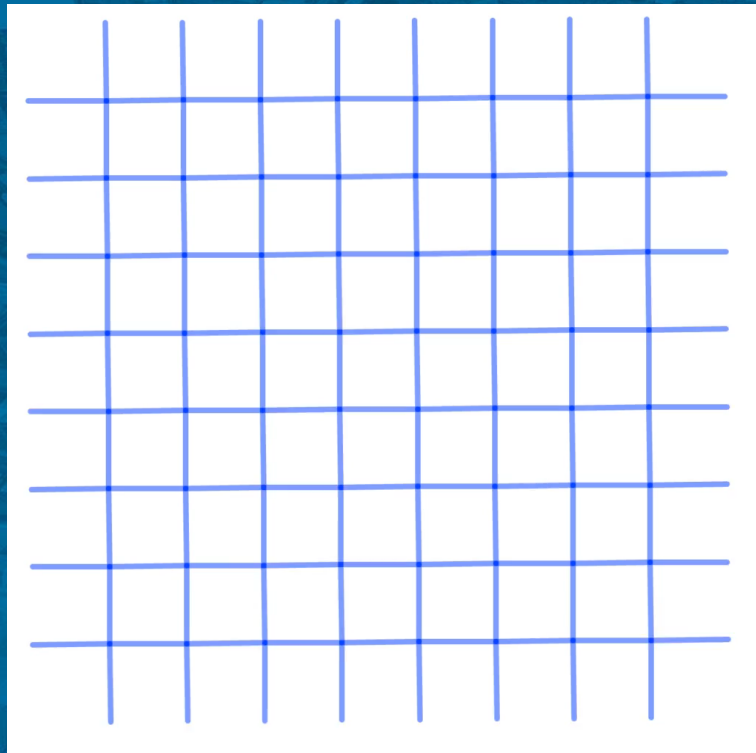
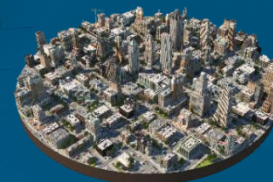
Impact of multi-
modal travel

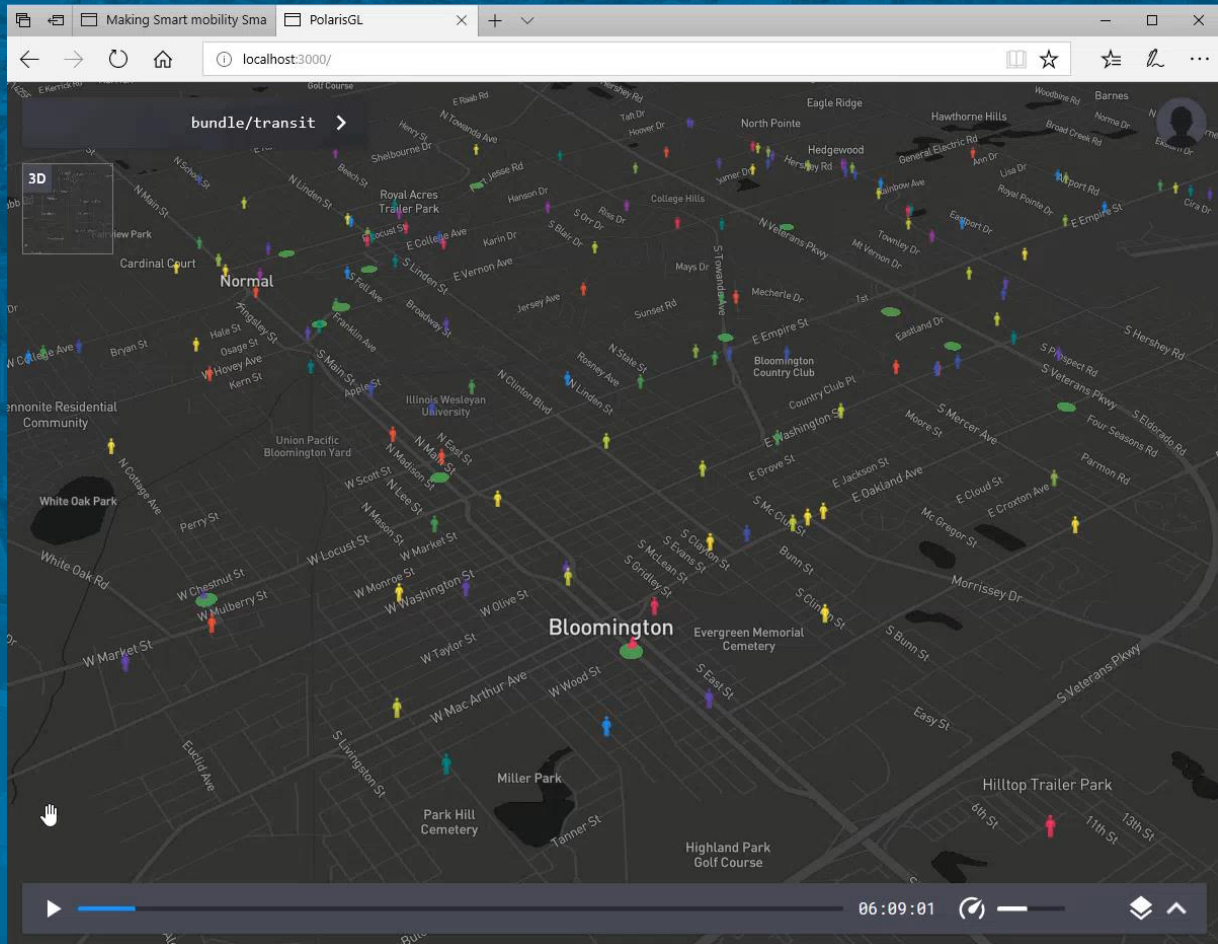
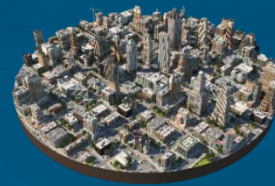
CAV impacts on value of time
and network performance

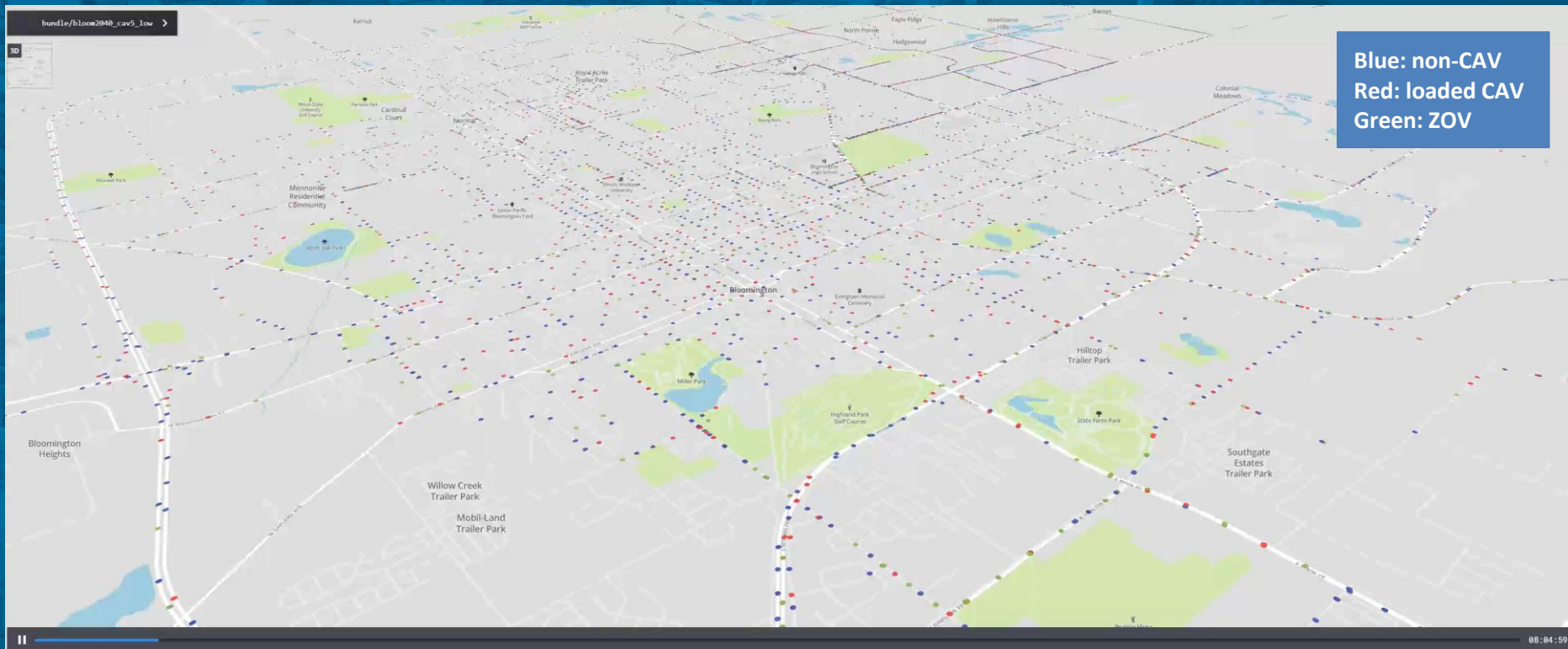
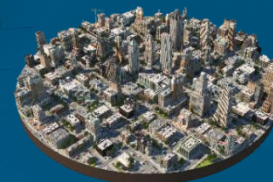


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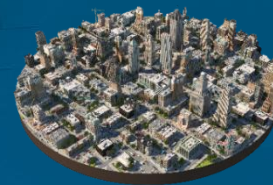
Platooning





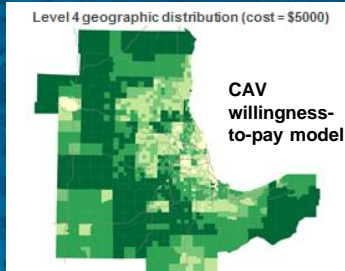


Energy Saved Might be Consumed by Additional Travel

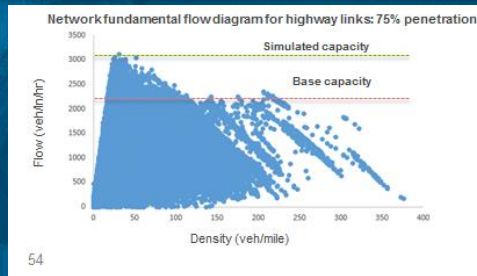
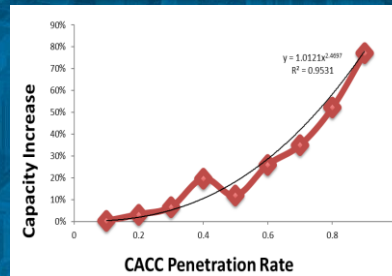


Travel Behavior Changes

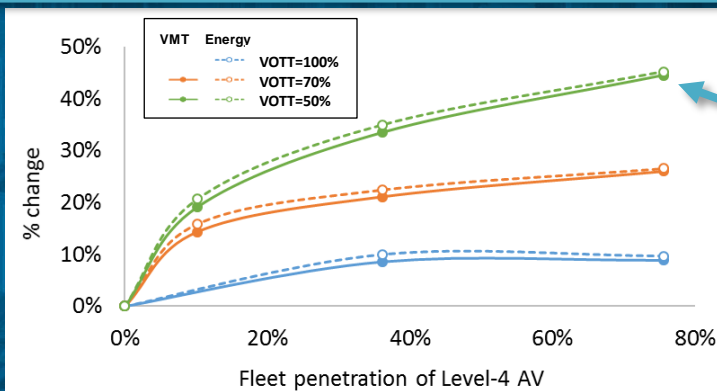
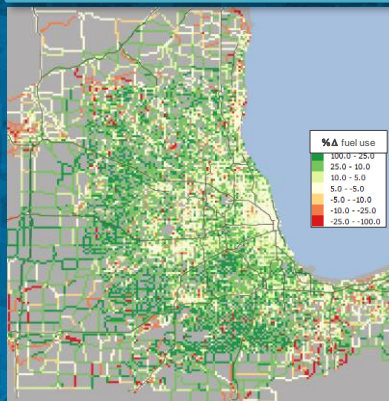
VOTT changes under CAV in literature	VOTT in CAV or of a non-driving passenger in a car
Litman, 2009	35% to 70% of the wage rate
Schrank et al., 2012	\$16 per hour
Bierstedt et al., 2014	25% to 50% of the wage rate
Gucwa, 2014	50% of the VOTT of the driver to VOTT in high-speed rail



Traffic Flow Changes

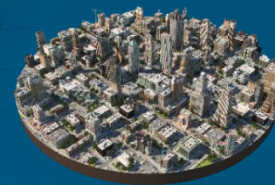


Scenario results



~45% increase in fuel use in high penetration, low VOT scenario

High Efficiency & High Throughput Enabled by HPC



Clusters



Super-Computer



First Exascale Machine in
2021 @ ANL

**COST BENEFIT
ANALYSIS: 12,000
cases, 64 cores/case**

	Mira	Cluster
cases per ensemble	12000	16
cores per ensemble	768000	1024
time to science	4 days	6 months
total core-hr cost	\$270K	\$230K

Using Machine Learning to Estimate Vehicle Energy Consumption under Various Trip Scenarios

Estimate energy consumption on both standard and real world driving cycles using ML

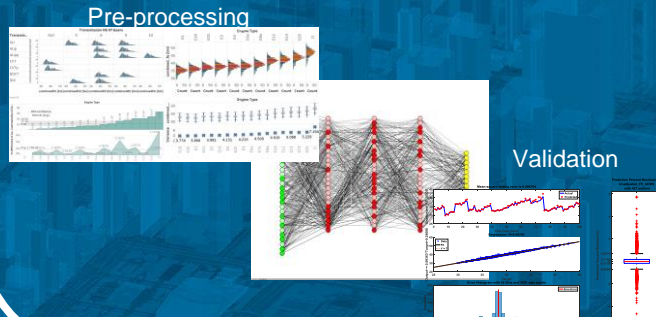
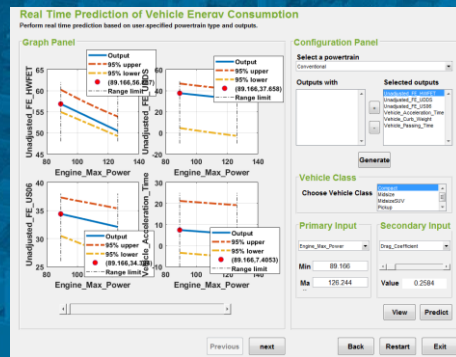
Machine Learning Tool / Workflow

US Standard Cycles

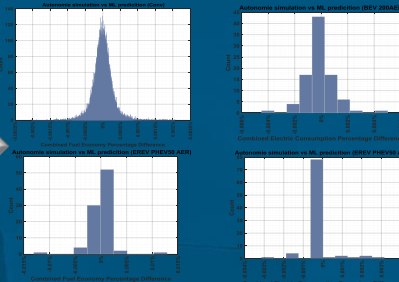
Autonomie Simulation Results
(>1.5M combinations across 10 vehicle classes)

Real World Cycles

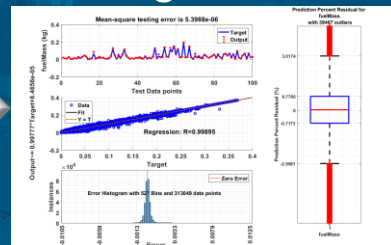
Autonomie Simulation Results
(from POLARIS & RWDC)
UofM MTC
FOA On-Road data



Excellent Prediction



Work in Progress,
promising first results



AMBER Seamlessly Integrate New Workflows

Smart Mobility Example

